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Where to place which sensor to measure sedentary behaviour? A method development and comparison among various sensor placements and signal types

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Abstract

Background: Sedentary Behaviour (SB) is associated with several chronic diseases and especially office workers are at increased risk. SB is defined by a sitting or reclined body posture with an energy expenditure ≤1.5 METs. However, current objective methods to measure SB are not consistent with its definition. There is no consensus on which sensor placement and type to be used.

Aim: To compare the accuracy of newly developed artificial intelligence models for 15 sensor placements in combination with four signal types (accelerometer only/plus gyroscope and/or magnetometer) to detect posture and physical in-/activity while desk-based activities.

Method: Signal features for the model development were extracted from sensor raw data of 30 office workers performing 10 desk-based tasks, each lasting 5 minutes. Direct observation (posture) and indirect calorimetry (in-/activity) served as reference criteria. The best classification model for each sensor was identified and compared among the sensor placements, both using Friedman and post-hoc Wilcoxon tests (p≤0.05).

Results: Posture was most accurately measured with a lower body sensor, while in-/activity was most accurately measured with an upper body or waist sensor. The inclusion of additional signal types improved the posture classification for some placements, while the acceleration signal already contained the relevant signal information for the in-/activity classification. Overall, the thigh accelerometer most accurately classified desk-based SB.

Conclusion: This study favours, in line with previous work, the measurement of SB with a thigh worn accelerometer, and adds the information that this sensor is also accurate in measuring physical in-/activity while sitting and standing.

Key Words: Accelerometer, Indirect Calorimetry, Inertial-Measurement-Unit, Machine Learning, Physical In-/Activity Classification, Posture Classification

Introduction

Due to the associated detrimental health effects, Sedentary Behaviour (SB) gets an increasing attention from the research community. SB is an omnipresent behaviour and integral part of the modern lifestyle (Loyen et al., 2017; Matthews et al., 2018). Especially in the office sector, where a large part of the population works (Keown, Skeaff, Perry, Haszard, & Peddie, 2018; Nooijen et al., 2018). Several chronic lifestyle diseases like diabetes and metabolic syndrome are associated with SB (Amirfaiz & Shahril, 2019; van der Velde et al., 2018). Accordingly, the use of active workplaces is currently recommended (Buckley et al., 2015), although there is a lack of evidence whether they have an impact on health (Neuhaus et al., 2014; Shrestha et al., 2018; Tew, Posso, Arundel, & McDaid, 2015). One important reason for this lack is the use of inconsistent and non-objective SB measurements (Hutcheson, Piazza, & Knowlden, 2018; Stephenson, McDonough, Murphy, Nugent, & Mair, 2017). While medicine is very skilled in diagnosing the diseases, measuring the dose of SB is still in its infancy and it is too early to establish evidence based health recommendations on SB (Stamatakis et al., 2019; van Uffelen et al., 2010).

By definition, SB involves a certain body posture (sitting or reclining) and a certain energy expenditure (≤1.5 Metabolic Equivalents, MET) (SBRN, 2012). However, SB is currently not measured in line with this definition (Fanchamps, van den Berg-Emons, Stam, & Bussmann, 2017; Holtermann et al., 2017; Kang & Rowe, 2015). Existing devices can be separated into two groups, those measuring posture, and those measuring activity (Kang & Rowe, 2015). This makes the SB measurement an unresolved challenge since both, the posture and activity, must be measured at the same time (Holtermann et al., 2017). Posture-based accelerometers are typically attached to the thigh (Grant, Ryan, Tigbe, & Granat, 2006; Skotte, Korshoj, Kristiansen, Hanisch, & Holtermann, 2014), and the recorded acceleration is low-pass filtered to determine the thigh orientation versus gravity (often referred to as inclinometer, Edwardson et al., 2017). These devices are known to have a very high sensitivity and specificity to detect sitting and standing (Y. Kim, Barry, & Kang, 2015; Stemland et al., 2015). However, they are not able to separate active from inactive sitting and standing (Godfrey, Culhane, & Lyons, 2007; Grant et al., 2006). Their SB estimate is based on the posture information only (Edwardson et al., 2016; Y. Kim et al., 2015). In contrast, activity-based devices are typically worn on a belt around the waist. Since recently, these sensors are also worn like a watch at the wrist with the aim to increase compliance (Kerr et al., 2017). For both placements, the recorded acceleration signal is converted into counts-per-minute, and used as a measure for the activity level (Migueles et al., 2017; Rosenberger et al., 2013). Activity-based devices are known to have a high accuracy to detect physical activity, i.e. light, moderate and vigorous intensity activities (Rothney, Schaefer, Neumann, Choi, & Chen, 2008). However, their SB estimate is based on a lack of activity only (Migueles et al., 2017).

A simple solution to measure SB in line with its definition would be to combine a posture- and activity-based device (Ellingson, Schwabacher, Kim, Welk, & Cook, 2016). However, each study participant would then have to be equipped with two sensors, limiting the field of application and increasing the complexity of data processing. A more feasible solution would be to calibrate one single body worn sensor against posture and activity. Unfortunately, there is a lack of information where such a sensor should be worn, nor is it known which signal types are needed. So far, acceleration signals are used due to their ease of use. Accelerometers record in a respectable frequency over a long period while having only a small sensor housing. The technical advances in recent years allows nowadays including also gyroscopes and magnetometers to build so called inertial-measurement-units (IMUs). The ActiGraph Link (ActiGraph LCC, Pensacola, USA) for example includes a 3D accelerometer, a 3D gyroscope, and a 3D magnetometer, and the activPAL4 (PAL Technologies, Glasgow, SCO) includes a 3D accelerometer and a 3D magnetometer. However, it is not known whether the additional signal types are of any value for the SB classification.

The primary aim of the present study is to develop and compare new models for 15 sensor placements in combination with four signal types. As an exhaustive phase 1 study in the framework of Keadle et al. 2019, this study shall inform future phase 1 and 2 method developments in the choice of sensor placement and signal type for the measurement of SB in desk-based activities (Keadle, Lyden, Strath, Staudenmayer, & Freedson, 2019). The secondary aim is to provide the same information for the isolated detection of posture (i.e. sitting, standing, and walking) and in-/activity (≤1.5 MET/>1.5 MET).

Materials and Methods

This study calibrated 15 body worn IMU's against valid reference criteria for posture (direct observation) and physical activity (indirect calorimeter). Data recording took place between 12th September and 12th November 2018 at a university workplace in Winterthur (Switzerland). For each sensor placement and signal combination (accelerometer only, accelerometer plus gyroscope, accelerometer plus magnetometer, accelerometer plus gyroscope and magnetometer), a separate machine learning model was developed for the posture as well as the in-/activity classification in sitting and standing. The models were then combined to classify the behaviour on a minute-by-minute level into inactive sitting (equal to SB), active sitting, inactive standing, active standing, and walking.

Participants and Ethics

Thirty healthy office workers between 18 and 65 years with ≥70% employment level spending ≥50% of their working day at an office desk were recruited through flyer, mail and word of mouth. Persons with chronic or acute respiratory, neurological, or systemic diseases as well as a silicon allergy were excluded. Since subjects booked their appointment online, in- and exclusion criteria were checked upon arrival. Subjects confirmed that they refrained from eating and drinking sugary, caffeinated, and alcoholic beverages for 2 hours and refrained from sport for 12 hours. Every subject signed an informed consent prior to study inclusion. This binational project was approved by the ethics committee in Stockholm (DNR: 2018/554-31/1), and obtained a declaration of non-objection from the ethics committee in Zurich. Participants averaged 38.8 ±9.0 years, 174 ±8 cm tall, and 71.2 ±11.0 kg weight, and worked 40.5 ±6.6 hours a week, of which 86 ±11% at an office desk (self-reported). No adverse events occurred.

Procedure

Subjects were equipped with the IMUs and the indirect calorimeter. While familiarizing with the equipment, they filled out a questionnaire regarding the personal demographics. Subsequently, the aim of each task was orally explained before the measurement started. Task and condition order was randomized but two identical tasks and conditions never occurred in succession. After completing all tasks, the resting metabolic rate was measured for 10 minutes in a supine position on a padded yoga mat with head pillow.

Tasks and Conditions

Participants performed four tasks (Table 1) at a height adjustable office desk in three different conditions: Sitting on a conventional office chair (Vitra, Birsfelden, SUI), sitting on a saddle chair with elevated seat height (HAG Capisco, Flokk, Oslo, NOR), and standing (Figure 1). The saddle chair was

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only used for the keyboard task to challenge the posture classification. Together with the walking task, 10 tasks were recorded, each lasting 5 minutes. To account for different workplace designs, 2/3 of the study participants used a desktop PC with two 24” screens, and 1/3 used a Laptop with 15” screen. The execution of the tasks was not demonstrated nor standardized in any form. Subjects had to place the working material their own way, and every subject completed the tasks in their own speed. Subjects were allowed to change table and seat height at any time.

Table 1: Investigated tasks. Selection is based on previous studies investigating typical desk-based activities (Burns, Forde, & Dockrell, 2017; Ellegast et al., 2012; Grooten, Conradsson, Ang, & Franzen, 2013). An example of each task is shown in Figure 1.

Task	Instruction and Aim
Mouse	Playing a computer game with the mouse (Microsoft Mahjong) to investigate intensive mouse use.
Keyboard	Writing a text in Microsoft Word® to investigate intensive keyboard use (mouse use allowed).
Deskwork	Doing various short tasks with a physical folder and a Microsoft Excel® file (get the folder, search in it, do mental arithmetic, create tables, write notes, switch screen views) to investigate successive short tasks with and without computer.
Sorting	Open envelopes and stow the documents according to the instruction on the documents (in storage compartments or folders) to investigate successive manual tasks without computer.
Walking	Walking around on the floor to investigate non-stationary activities like walking to the printer or in a meeting.

Figure 1: Investigated office tasks (Mouse (a), Keyboard (b), Deskwork (c), and Sorting (d)) and conditions (conventional office chair (a, d), saddle chair (b), and standing (c)). Details for each task are given in Table 1.

Measurement Equipment

Reference Criterion

Direct observation was used as reference criterion for posture, and an indirect calorimeter (K5, cosmed, Rome, ITA) as reference criterion for activity. The K5 has been shown to measure the energy expenditure of a given task reliably (Crouter et al., 2019). It was calibrated before each recording according to manufacturer's recommendation (flowmeter, scrubber, and room air). Data was recorded in the mixing chamber mode with 0.1 Hz. VO_2 and VCO_2 was exported to a csv-file for subsequent processing.

Inertial-Measurement-Units

The MVN Biomech Awinda from Xsens (Enschede, NLD) in full body configuration without hands was used. The system consists of 15 small IMUs, each featuring a 3D accelerometer (range ±16g), a 3D gyroscope (range ±2000°/s), and a 3D magnetometer (range ±1.9 Gauss). The IMUs were placed according to manufacturer's recommendation on the following segments: Head, Sternum, and Waist (unilateral), Wrist, Upper Arm, Shoulder, Thigh, Shank, and Foot (bilateral). All units were attached with elastic stripes, except the shoulder and sternum (in a special shirt) as well as the waist (belt). The 60Hz data of the units were exported as mvnx-files for subsequent processing.

Data Processing

All data were loaded into MATLAB 2019a (version 9.6.0, MathWorks Inc., Nattick, USA) for processing and evaluation.

Reference Criterion

The energy expenditure was calculated using the Weir equation. Only steady state data was used to express the energy expenditure of each task. The onset of steady state was defined by the first minute with <10% deviation from the median of all subsequent minutes, but earliest after 1 minute and latest after 4 minutes. The median energy expenditure while steady state of each task was then put in relation to the resting metabolic rate to calculate the MET. The resting metabolic rate was defined as the median energy expenditure during the second five minutes in supine position (Borges et al., 2016; Popp, Tisch, Sakarcan, Bridges, & Jesch, 2016). All recorded minutes were subsequently assigned into body posture (sitting, standing, and walking) and in-/activity level (inactive: ≤1.5 MET, active: >1.5 MET).

Inertial-Measurement-Units

The IMU signals were also split into minute-by-minute data. For each minute, the same 562 signal features as in (Kuster et al., 2020) (except daytime) were calculated for each sensor type (feature calculation shown in Appendix 1). The machine learning was split in three parts: 1) Feature Filtering, 2) Feature Inclusion, and 3) Model Optimisation and Training. The processing was conducted separately for the posture classification, the in-/activity classification in sitting, and the in-/activity classification in standing. To generate the overall behaviour classification for SB, active sitting, inactive standing, active standing, and walking, the classification models of each sensor and signal combination were combined.

1) The feature filtering used a customized random forest classifier programmed in Python (program available at www…). Out of 100 classifier runs, the best 100 features were selected. The selection was done separately for each raw signal (accelerometer, gyroscope, and magnetometer). This step is

referred to as feature filtering as non-relevant features are filtered out so that the subsequent computational demanding steps did not need to examine the full feature list.

2) In order to include only the most relevant features, the remaining features were stepwise included into a random forest classifier with five trees, separately for each investigated signal combination (accelerometer only, accelerometer plus gyroscope, accelerometer plus magnetometer, accelerometer plus gyroscope and magnetometer). The first round selected the single best feature to solve the classification, and each subsequent round added the next best feature (Kuster et al., 2018). The stepwise inclusion was stopped when the maximum accuracy was reached (no increase for the next ten features).

3) The training architecture for the classification models were then optimized for each feature number using MATLAB's built in hyperparameter optimisation function for classification learners (fitcensemble with "OptimizeHyperparameters" set to "all", see Matlab Code in Appendix 2). The optimisation searched for the best learning algorithm, split criterion, number of learners, learning rate, minimum leaf size, and maximum number of splits. Further details about the parameter optimisation can be accessed online (https://mathworks.com/help/stats/fitcensemble.html). The optimized parameters were finally used to train the models. For each sensor and signal combination, the feature number with highest accuracy was selected and used in the statistical comparison.

Statistics

The feature inclusion and model training (including the parameter optimisation) required a cross-validation technique to identify the most accurate feature in each step. The leave-one-subject-out cross-validation technique was used for this. The technique trains a model on all but one subject (the leave-out), and analyses the model accuracy on the leave-out subject. This procedure is repeated until every subject served once as leave-out, and the accuracy is averaged over all leave-out subjects. To equally account for both, the true positive and true negative detection of SB, the balanced sensitivity and specificity, which is the mean of sensitivity and specificity, was used as the measure of accuracy (Ellis, Kerr, Godbole, Staudenmayer, & Lanckriet, 2016).

To identify the best signal combination for each sensor, a Friedman test for dependent data was used. Unless there was a significant effect of signal type, only the accelerometer results are presented. Otherwise, the best signal combination was identified with a post-hoc Wilcoxon test, taking multiple testing according to Bonferroni into account.

The accuracy among all sensor placements was compared with another Friedman test, again followed by a post-hoc Wilcoxon test adjusted for multiple testing. Sensor placement comparison was done separately for the accelerometers only and the best signal combinations. The accuracy is presented with median and non-parametric 95% Confidence Interval. For the isolated in-/activity classification in sitting and standing, the accuracy was merged since there were only two categories, and the sensitivity for inactivity equals the specificity for activity and vice-versa. Descriptive statistics is presented, after rejecting normal distribution with Lilliefors test, with median and inter-quartile range. Level of significance was set to 0.05.

Results

Out of 1'500 recorded minutes, seven minutes from three subjects were lost due to system malfunction. Overall, subjects spent 76.6% and 70.8% of all sitting and standing minutes inactive,

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respectively. The MET of each task and condition is shown in Table 2. The median (inter-quartile range) resting metabolic rate was 1'696 (607) kcal × day^{-1} or 3.5 (0.9) ml × kg^{-1} × min^{-1} VO_2.

Table 2: Average Metabolic Equivalent (MET) and proportion of time spent inactive for each condition and task.

			Conditions			
			Conventional Chair	Saddle Chair	Standing	Walking
Tasks	Mouse	MET	1.19 (0.20)		1.18 (0.25)	
		% ≤1.5 MET	96.7		100.0	
	Typing	MET	1.34 (0.29)	1.2 (0.27)	1.28 (0.16)	
		% ≤1.5 MET	93.3	96.7	90.0	
	Deskwork	MET	1.26 (0.29)		1.33 (0.25)	
		% ≤1.5 MET	76.7		76.7	
	Sorting	MET	1.72 (0.42)		1.75 (0.33)	
		% ≤1.5 MET	16.7		16.7	
	Walking	MET				3.30 (0.91)
		% ≤1.5 MET				0.0

Metabolic Equivalent (MET) is presented with median and inter-quartile range in brackets, proportion of time spent inactive (≤1.5 MET) in percentage.

The best accelerometer placement to classify SB in desk-based activities was the right thigh. The results for the left thigh and the two shank accelerometers were similar (marked in grey in Table 3), while all other accelerometers performed significantly worse to detect SB as well as inactive standing. However, when adding the gyroscope and magnetometer data to the waist, the accuracy significantly increased and was no longer different from the right thigh accelerometer. In contrast to the inactive behaviours, the accuracy to classify active sitting and standing was the same for most placements, and all accelerometer placements were able to detect walking with 100.0% accuracy (data not shown in Table 3). All models in table 3 are shared on MATLAB Central (www….).

If looking only at the posture classification, it gets evident that the thigh placement classified posture most accurate, followed by the shank placement (Table 4). All other accelerometer placements performed significantly worse. Even when adding the gyroscope and magnetometer data to the waist, which improved the posture classification, the waist placement was not as accurate as the thigh. To detect the in-/activity level in sitting and standing, the sternum (sitting) and head (standing) placement performed best (Table 4). For sitting, those sensors placed at the upper body (except the right wrist) showed a significantly higher accuracy than those placed at the lower body and waist. For standing, the differences between the placements were only marginally and non-significant. For both, the in-/activity classification in sitting and standing, adding the gyroscope and magnetometer data improved the accuracy only for one single placement in sitting (right shank).

Table 3: Accuracy of sensor placement and signal type (accelerometer only, and best signal combination) to classify desk based activities into posture and physical in-/activity level in sitting and standing (inactive: ≤1.5 MET, active: >1.5 MET). Sedentary Behaviour is equal to inactive sitting.

	Sedentary Behaviour			**Active Sitting**			**Inactive Standing**			**Active Standing**		
	Accelerometer	Best Signal Combination		Accelerometer	Best Signal Combination		Accelerometer	Best Signal Combination		Accelerometer	Best Signal Combination	
Sensor	Accuracy	Accuracy	Type	Accuracy	Accuracy	Type	Accuracy	Accuracy	Type	Accuracy	Accuracy	Type
Waist	84.9 [80.0 - 88.9]*	91.9 [88.0 - 93.2]	+ G + M	87.8 [83.0 - 90.7]			85.7 [82.3 - 88.3]*	91.9 [89.2 - 94.6]	+ G + M	90.0 [86.3 - 98.9]		
Thigh (right)	**93.4 [91.1 - 96.3]**			**92.9 [89.6 - 97.9]**			**95.0 [93.3 - 96.8]**			**96.0 [80.0 - 100.0]**		
Thigh (left)	91.7 [87.6 - 94.0]	95.0 [91.8 - 97.5]	+ G	90.0 [80.8 - 97.9]			93.1 [90.5 - 96.1]	96.7 [93.2 - 100.0]	+ G	93.0 [89.6 - 98.9]		
Wrist (right)	75.0 [68.5 - 79.8]*			72.2 [61.8 - 94.5]*			60.0 [56.1 - 69.1]*			80.0 [76.1 - 91.2]*		
Wrist (left)	75.1 [70.0 - 78.3]*			89.4 [71.6 - 96.2]			68.5 [62.1 - 76.8]*			80.0 [75.0 - 94.6]		
Sternum	83.7 [78.7 - 86.8]*			88.9 [78.4 - 96.2]			81.0 [75.2 - 85.6]*			87.8 [78.5 - 95.7]	90.0 [87.2 - 97.9]	+ G + M
Head	71.7 [65.3 - 73.8]*	81.5 [79.2 - 85.0]*	+ G + M	69.4 [57.8 - 90.0]*	88.9 [74.8 - 95.7]	+ G	65.3 [59.2 - 68.3]*	85.2 [80.1 - 91.8]*	+ G + M	85.9 [72.2 - 96.2]		
Shoulder (right)	82.0 [76.7 - 86.2]*			86.1 [70.7 - 94.7]			82.5 [75.1 - 87.0]*			85.2 [78.8 - 91.5]	92.8 [85.6 - 98.3]	+ G + M
Shoulder (left)	83.3 [80.5 - 88.3]*	87.8 [83.1 - 92.8]*	+ G + M	89.4 [78.4 - 91.7]	92.0 [87.8 - 98.9]	+ G + M	82.9 [76.7 - 87.0]*			89.4 [78.2 - 96.2]		
Upper Arm (right)	78.0 [75.2 - 82.3]*			86.1 [76.1 - 92.8]			73.8 [68.8 - 76.8]*			83.3 [72.4 - 90.4]		
Upper Arm (left)	77.0 [70.7 - 81.2]*			81.6 [70.0 - 96.2]			71.0 [65.0 - 74.9]*			86.5 [76.6 - 90.0]		
Shank (right)	91.8 [89.1 - 95.0]	96.2 [94.2 - 98.1]	+ G	85.6 [77.8 - 96.2]	90.0 [80.8 - 98.3]	+ G	91.0 [85.6 - 94.5]			93.0 [87.9 - 99.3]		
Shank (left)	90.0 [87.5 - 94.3]			86.2 [70.0 - 92.7]	89.4 [80.8 - 97.8]	+ M	90.9 [87.4 - 92.8]			89.4 [76.8 - 95.4]		
Foot (right)	81.7 [78.0 - 87.0]*			70.0 [65.5 - 87.1]*			76.3 [71.5 - 82.8]*			87.8 [74.8 - 90.7]*		
Foot (left)	82.3 [76.4 - 86.7]*	88.7 [86.4 - 91.8]*	+ G + M	77.8 [66.7 - 85.0]*			79.8 [73.4 - 83.0]*			83.0 [74.1 - 95.7]*		

Indicated is the median balanced sensitivity and specificity with 95% Confidence Interval in brackets. The column "Best Signal Combination" indicates whether the addition of the gyroscope (+ G) and/or magnetometer (+ M) significantly improved the accuracy (empty if not). The accelerometer accuracy with lowest rank sum (Friedman test) of each behaviour is marked in bold, and those non-significantly different in grey / those significantly different with asterisk.

Table 4: Accuracy of sensor placement and signal type (accelerometer only, and best signal combination) to classify desk based activities separately into posture (sitting and standing) and physical in-/activity level (inactive: ≤1.5 MET, and active: >1.5 MET)

	Posture Classification						**In-/Activity Classification**					
	Sitting			**Standing**			**Sitting**			**Standing**		
	Accelerometer	Best Signal Combination		Accelerometer	Best Signal Combination		Accelerometer	Best Signal Combination		Accelerometer	Best Signal Combination	
Sensor	Accuracy	Accuracy	Type	Accuracy	Accuracy	Type	Accuracy	Accuracy	Type	Accuracy	Accuracy	Type
Waist	89.6 [86.0 - 94.0]*	94.0 [91.3 - 98.0]*	+ G + M	90.0 [87.2 - 92.5]*	95.0 [91.1 - 98.3]*	+ G + M	90.0 [83.2 - 95.0]*			92.9 [80.0 - 100.0]		
Thigh (right)	**100.0[99.3-100.0]**			**100.0 [99.1-100.0]**			90.0 [85.0 - 95.7]*			92.5 [80.0 - 100.0]		
Thigh (left)	98.0 [98.0 - 100.0]	100.0 [100.0 -	+ G	97.9 [97.5 - 100.0]	100.0 [100.0 -	+ G	86.3 [78.2 - 95.3]*			90.0 [85.0 - 96.7]		
Wrist (right)	68.0 [62.0 - 74.7]*			66.7 [58.9 - 72.5]*			90.8 [75.0 - 97.5]*			92.9 [83.2 - 96.7]		
Wrist (left)	74.0 [69.6 - 78.0]*			72.9 [66.6 - 78.3]*			97.2 [86.6 - 100.0]			96.7 [81.3 - 100.0]		
Sternum	82.0 [79.3 - 84.5]*			80.0 [77.5 - 85.3]*			**96.2 [90.0 - 100.0]**			91.3 [85.0 - 96.4]		
Head	67.0 [62.0 - 70.7]*	88.0 [80.0 - 90.0]*	+ G + M	65.0 [59.7 - 69.6]*	90.0 [81.5 - 91.7]*	+ G + M	90.0 [82.4 - 95.0]			**95.6 [86.1 - 100.0]**		
Shoulder (right)	83.0 [76.0 - 88.0]*	86.0 [82.0 - 90.0]*	+ M	84.2 [76.4 - 86.1]*	84.6 [79.7 - 90.0]*	+ M	94.4 [85.0 - 100.0]			91.3 [84.4 - 100.0]		
Shoulder (left)	84.0 [80.0 - 88.0]*	92.0 [87.3 - 94.7]*	+ G + M	84.6 [78.9 - 87.5]*	92.1 [87.1 - 93.9]*	+ G + M	90.5 [86.6 - 97.5]			96.5 [80.0 - 100.0]		
Upper Arm (right)	75.0 [71.3 - 79.9]*			73.3 [70.0 - 78.9]*			92.4 [83.5 - 100.0]			91.3 [83.6 - 97.9]		
Upper Arm (left)	76.0 [70.0 - 78.0]*			72.5 [70.0 - 75.6]*	79.6 [74.2 - 82.8]*	+ G + M	91.0 [83.2 - 100.0]			91.7 [86.1 - 96.7]		
Shank (right)	97.9 [92.0 - 98.0]*	100.0 [98.0 -	+ G + M	97.5 [93.0 - 98.3]*	98.3 [97.5 - 100.0]	+ G	88.0 [78.2 - 90.9]*	90.0 [83.6 - 97.2]	+ G	92.9 [81.3 - 100.0]		
Shank (left)	96.8 [94.0 - 98.7]			97.1 [94.2 - 98.9]			83.5 [70.0 - 91.8]*			85.0 [76.7 - 92.8]		
Foot (right)	82.0 [80.0 - 86.0]*			81.7 [78.0 - 83.6]*			87.5 [79.1 - 93.1]*			84.2 [75.0 - 90.0]		
Foot (left)	84.0 [82.0 - 86.7]*	90.0 [83.9 - 92.7]*	+ G + M	81.3 [80.0 - 86.1]*			82.9 [71.6 - 90.0]*			80.6 [75.0 - 96.7]		

Indicated is the median balanced sensitivity and specificity with 95% Confidence Interval in brackets. The column "Best Signal Combination" indicates whether the addition of the gyroscope (+ G) and/or magnetometer (+ M) significantly improved the accuracy (empty if not). The accelerometer accuracy with lowest rank sum (Friedman test) of each behaviour is marked in bold, and those non-significantly different in grey / those significantly different with asterisk.

Discussion

This study compared the accuracy of 60 sensor placement-signal type combinations to classify SB as well as active sitting, inactive standing, active standing, and walking. The results of this study support future, more field-like method developments and algorithm refinements for SB in the choice of sensor placement and signal type. Furthermore, the study also presents the isolated posture as well as the in-/activity classification.

Over all, the SB classification was most accurately solved by the thigh and shank accelerometers as well as the waist IMU. In particular, the classification of SB and inactive standing strongly depended on sensor placement, while the placement dependence was less pronounced for the active behaviours, regardless of body posture. The isolated analysis of posture and in-/activity uncovers that the difference results mainly from the posture classification. The thigh and shank accelerometers solved this classification significantly best, even when adding the gyroscope and/or magnetometer data to the other placements. This result demonstrates that posture is best measured with a sensor worn on the lower extremity, while the accelerometers attached to the upper extremity and trunk performed better to detect the in-/activity level, in particular for sitting. Presumably, this is due to the fact that the activity in sitting is mainly caused by upper body motions that are less easy to detect with sensors worn at the lower extremities. But still, even the lower body sensors were able to detect the activity level to a certain amount, presumably because upper body motions raising the MET level above 1.5 cause a certain motion pattern of the lower body the models learned to detect. Interestingly, the inclusion of additional sensor signals has not improved the in-/activity classification. We therefore conclude that the acceleration contains already the relevant signal information to solve the in-/activity classification. In contrast, the inclusion of additional sensor signals improved the posture classification for some sensor placements (e.g. waist, table 4). Overall, SB was most often confused with inactive standing, and inactive standing with SB, and the active behaviours were confused with the inactive behaviours in the same posture (see misclassification table in Appendix 3).

So far, three accelerometer placements are commonly used to measure SB: the thigh, the waist, and the wrist (Matthews, Hagstromer, Pober, & Bowles, 2012). In the present study on detecting SB in desk-based office work, the thigh accelerometer significantly outperformed the other two accelerometer placements. However, previous studies used the thigh sensor as a posture-based method only (Y. Kim et al., 2015; Skotte et al., 2014). This study shows, in contrast, that an accelerometer worn on the thigh is also accurate in measuring the in-/activity level, in sitting as well as in standing. The presented data suggest that the combination of an accelerometer and a gyroscope might perform even better than an accelerometer only (results for left thigh in table 3), but future studies are needed to draw a sound conclusion. However, the inclusion of a magnetometer as e.g. can be found in the new activPAL4 did not improve the SB classification. In contrast, the waist accelerometer alone performed significantly worse, and the combination with data of a gyroscope and magnetometer significantly improved the posture and thus the SB classification. Accordingly, if a future study wants to calibrate a waist worn sensor to measure SB, we recommend the use of a 9 dimensional IMU, e.g. like the ActiGraph Link. However, it must be noted that the waist worn IMU was the only sensor with lower accuracy to detected the standing-like sitting posture on the saddle chair as compared to the normal sitting posture on the conventional chair, and that the waist worn IMU model uses much more features than the thigh worn accelerometer model (Appendix 4). The presented data show that the wrist placement is accurate to classify the activity level, but we noticed a limited accuracy to measure posture and thus SB. The inclusion of additional sensor signals has not improved the accuracy of the wrist placement. This makes the wrist placement not the preferred choice to measure SB from an accuracy perspective.

In this regard, it is important to note that the accuracy is only one aspect on which the choice of sensor placement and signal type should be based. Other important and more pragmatic aspects include sensor pricing, wear comfort, protocol compliance, and the primary study aim. Since each sensor placement has its own pros and cons, there is no placement that outperforms all others. A large-scaled epidemiological study focusing on the total time spent sedentary a day might has to use another method than a workplace intervention study aiming to break up prolonged SB. The former might consider comfort and compliance most important, while the latter has to ensure a high accuracy to detect behavioural changes. However, in any case, both studies should base their sensor placement and signal type decision on the available evidence, and have to discuss their findings in terms of the decisions made, be it a limited accuracy or a pragmatic limitation in data recording.

Methodological Considerations

This study examined the fundamental accuracy of different sensor placements, whether accelerometers or IMUs, to detect body posture and in-/activity level while typical desk based activities in line with the definition of SB. For this reason, the study used a university workplace with prescribed activities to ensure a safe handling of the indirect calorimeter and the motion capture system. Other studies used direct observation as the only reference criterion for the SB classification in combination with the Compendium of Physical Activity (Ainsworth et al., 2011; Lyden, Keadle, Staudenmayer, & Freedson, 2014). Direct observation allows for a much more field-like data recording, however, it classifies seated activities as SB, and non-seated activities as non-SB. This in fact turns the SB classification into a posture classification and neglects the MET component of SB. The protocol used in this study classified the posture and in-/activity level independently and individually. The same task could be classified for one subject as SB and for another as active sitting, and each task was performed in sitting as well as in standing (Table 2). This stays also in contrast to the vast majority of calibration studies that used a predefined SB classification on task level, with only a minority of sedentary tasks and an artificial large gap between the prescribed sedentary and non-sedentary tasks in terms of posture and in-/activity (e.g. Montoye, Pivarnik, Mudd, Biswas, & Pfeiffer, 2016; Staudenmayer, He, Hickey, Sasaki, & Freedson, 2015; Zhang et al., 2012). As a consequence, the trained models in these studies detect SB through a correctly classified posture or in-/activity level, while the models trained in this study detect SB through a correctly classified posture and in-/activity level. Accordingly, the accuracies presented in this study for the thigh, waist and wrist are lower than those presented in other studies, but expected to be much closer to reality where SB is very common, not every sitting is necessarily SB, and the separation between SB and non-SB is not always that obvious. Furthermore, to account for the variability in real-life, the prescribed tasks were not standardized, only orally explained without demonstration, and 1/3 of the study population used a Laptop while 2/3 used a desktop computer. No differences between the two workplaces were found.

The indirect calorimeter used to measure the MET level requires a steady state to determine the true energy expenditure. With three pilot subjects doing 17 tasks, we observed that steady state was typically reached after two, but no later than four minutes. Consequently, the subjects of this study performed each activity for five minutes, and each minute was categorized into in-/active behaviour using the steady state energy expenditure and a cut-point of 1.5 MET. Contrary to the Terminology

Consensus Project of the Sedentary Behavior Research Network (Tremblay et al., 2017), the 1.5 MET cut-point was also applied to separate in-/active standing as we see no evidence that this cut-point should be higher for standing than sitting. In our data, there was no MET difference with respect to body posture, and the time spent >1.5 MET should be considered light physically active regardless of posture. To calculate the MET, the steady state energy expenditure of each task was referenced to the resting metabolic rate (Kozey, Lyden, Staudenmayer, & Freedson, 2010). Most calibration studies used a standardized MET of 3.5 ml × kg^{-1} × min^{-1} VO_2 or an approximated MET based on personal characteristics (D. Kim et al., 2017; Kozey et al., 2010). However, both neglect individual variation and ambient factors like temperature (Borges et al., 2016; Popp et al., 2016). Although the resting metabolic rate was on average 3.5 ml × kg^{-1} × min^{-1} VO_2, the results of the present study should not be interpreted as if the standardized value was taken.

To record the body worn sensor signals, the Xsens Biomech Awinda was used. The system is a user-friendly whole body measurement system allowing to record with 15 IMUs synchronously. However, the recording frequency cannot be adjusted (set to 60Hz). The subjects in this study additionally wore four standalone MSR145 accelerometers (MSR Electronics GmbH, Seuzach, SUI) recording with 20Hz at both thigh, the waist and the sternum (range ±2g). With exactly the same data processing, the developed models for these sensors showed the same significances as the presented models. From this observation, we conclude that the presented differences between the sensor placements do not depend on the sensor manufacturer nor the recording frequency and the recording range, as long as a model is used with the same sensor as it was developed with.

To develop simple classification models with only relevant features, the study used a stepwise feature inclusion. The stepwise feature inclusion is a wrapper method that identifies the most relevant feature set with consideration of the final model algorithm. However, the method has two significant limitations. First, it is computationally very expensive. This is why it was combined with a previous feature filtering to limit the number of features to be inspected. Second, every step requires a performance analysis to identify the most relevant feature. This requires a cross-validation approach like the leave-one-subject-out. The leave-one-subject-out approach provides a good estimate for the model performance in the recorded data, but other studies reported a 0-15% overestimation for the model generalisability to new data (Gyllensten & Bonomi, 2011; Kerr et al., 2016; Montoye, Westgate, Fonley, & Pfeiffer, 2018). These studies also reported a substantially smaller overestimation for sitting and standing than for walking, running and cycling. Accordingly, we expect that the overestimation is closer to 0% than 15%, but it is impossible to make a reliable conclusion unless an independent field validation is conducted. Since the overestimation applies equally to all models, we consider the observed differences to be accurate, and the values presented in table 3 and 4 could be interpreted in terms of model generalisability as maximum accuracies that can be reached. An alternative solution to estimate the model generalisability would be to split the sample in a training and testing set, and report only the accuracy in the testing set. However, this would generate a similarly biased estimation of the generalisability as the testing set was recorded in exactly the same setting than the training set. Furthermore, splitting the sample means decreasing the training sample and thus weakening the model development. To analyse the models' generalisability to new data, it is essential to perform an independent field validation. However, there are three main reason why this was not included in the present study. First, this study aimed to compare the fundamental accuracy of various sensor placements and signal types to inform future phase 1 and 2 algorithm developments and refinements, and not to present a field-ready classification model (Keadle, Lyden, Strath, Staudenmayer, &

Freedson, 2019). Second, the sensors of the motion capture system record only for a limited amount of time (up to 8 hours), require a wireless connection to a computer, and the system does not allow to record with a user-specified number of sensors. Accordingly, the systems' usability in field studies is severely limited, but it's usability in the present study was very high. Third, there is still no valid reference criteria to measure physical in-/activity in desk based office work on an individual subject level in field settings. With respect to future method developments and validations, we see an urgent need of having such a method. We therefore highly recommend to analyse whether steady-state detection algorithms for indirect calorimetry data as used in other research areas (e.g. the analysis of steady-state energy expenditure with variable walking speeds, Plasschaert, Jones, & Forward, 2009; Schwartz, 2007) could be adapted to our field of research. An independent field validation without such a method is pointless for the presented models. In this regard, it should generally be considered more critical that measuring SB is often equated with measuring sitting (when using a posture-based device) or a lack of physical activity (when using an activity-based device), but in both cases interpreted as it would be inactive sitting. For posture-based devices, we recommend to talk about "sitting", and for activity-based devices, we recommend to talk about "minimal physical activity" (Holtermann et al., 2017). This study therefore does not only present the SB accuracy, but also the accuracy for the isolated posture and in-/activity classification for each sensor placement and signal type. This information might be useful for future studies to uncover the relevance of the two aspects of SB: posture and physical inactivity.

All developed models were at last statistically compared to identify the one with highest accuracy for each placement. We thereby took into account that the inclusion of an additional signal type makes the sensor more expensive and the data processing more complex. Unless there was a significant improvement, only the accelerometer results are presented. Furthermore, this study started with a very large feature set informed by previous studies in this field of research, and calculated each feature for each signal type. Since previous studies used almost exclusively accelerometers, there might be other features more suitable for the gyroscope and magnetometer data. It remains subject to future studies to investigate whether the inclusion of other signal features for those two sensor types improves the classification accuracy. Last, the numbers presented in table 3 and 4 are based on equally fractioned office tasks although it is unlikely that office workers spend their time equally balanced in real life. The interested reader therefore finds in Appendix 5 the accuracy of each sensor placement and signal type separated by behaviour and office task. From this table, they can inform their selves about the most accurate sensor placement in relation to the expected behaviour in a future data collection.

Conclusion

The presented method development and comparison shows that posture is best measured with lower body sensors, while upper body sensors performed better to detect the in-/activity level, in particular for sitting. The study also shows that the acceleration signal contains the relevant signal information to solve the in-/activity classification, while the inclusion of additional sensor signals improved for some placements the posture classification. Future, more field-like algorithm developments and refinements should consider the results of this study in combination with pragmatic aspects derived from field studies as a basis for decision-making when choosing sensor placement and signal type. In line with previous work (Kozey-Keadle, Libertine, Lyden, Staudenmayer, & Freedson, 2011; Montoye et al., 2018), this study favours the measurement of SB with a thigh worn accelerometer, and adds the information that such a sensor is also accurate in measuring the in-/activity level in sitting and standing.

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Appendix 1: Table of all features used in this study, including instruction on how they were calculated in MATLAB 2019a (version 9.6.0, MathWorks Inc., Nattick, USA). Each Feature was calculated for each sensor type separately (accelerometer, gyroscope, and magnetometer) among all 11 dimensions (rawdata, vector magnitude, filtered data, and angles), except both DTW and the Covariance/Correlation between axes (only for raw data). Features marked with * were replaced with zero in case their value was not defined. Column 4 specifies the feature abbreviation as used in Appendix 4.

Dimensions	Instructions / MATLAB Code
rawdata: RAWDATA(:,1:3)	x, y, and z, as recorded
vector magnitude: RAWDATA(:,4)	= sqrt(RAWDATA(:,1).^2+RAWDATA(:,2).^2+RAWDATA(:,3).^2)
filtered data: RAWDATA(:,5:8)	= filter(b,a, RAWDATA(:,1:4)); with CutoffFreq = 0.5; sampfreq = 30; [b,a] = butter(2,CutoffFreq / (sampfreq/2));
filtered angle x: [~,RAWDATA(:,9),~]	= cart2sph(RAWDATA(:,6),RAWDATA(:,7),RAWDATA(:,5));
filtered angle y: [~,RAWDATA(:,10),~]	= cart2sph(RAWDATA(:,7),RAWDATA(:,5),RAWDATA(:,6));
filtered angle z: [~,RAWDATA(:,11),~]	= cart2sph(RAWDATA(:,5),RAWDATA(:,6),RAWDATA(:,7));

#	Features	MATLAB Code	Abbreviation
11	1st Percentile	prctile(MinData,1);	1st Percentile
11	5th Percentile	prctile(MinData,5);	5th Percentile
11	10th Percentile	prctile(MinData,10);	10th Percentile
11	25th Percentile	prctile(MinData,25);	25th Percentile
11	50th Percentile (Median)	prctile(MinData,50);	50th Percentile
11	75th Percentile	prctile(MinData,75);	75th Percentile
11	90th Percentile	prctile(MinData,90);	90th Percentile
11	95th Percentile	prctile(MinData,95);	95th Percentile
11	99th Percentile	prctile(MinData,99);	99th Percentile
11	Inter-quartile range	iqr(MinData)	iqr
11	Minimum	min(MinData);	min
11	Maximum	max(MinData);	max
11	Range	max(MinData) - min(MinData);	Range
11	Mean	nanmean(MinData);	Mean
11	Standard Deviation (SD)	nanstd(MinData);	std
11	Coefficient of Variation (CV) *	nanstd(MinData)./nanmean(MinData);	CoeffVariation
11	Skewness *	skewness(MinData);	Skewness
11	Kurtosis *	kurtosis(MinData);	Kurtosis
11	Summed absolute Signal Change from Frame to Frame	sum(abs(diff(MinData)));	abs SignalChange
11	Lag 1 Frame Autocorrelation *	lag = autocorr(MinData,sampfreq); lag(2);	Lag1Autocorr
11	Lag 1 Second Autocorrelation *	lag = autocorr(MinData,sampfreq); lag(sampfreq+1);	Lag1secAutocorr
11	3rd Central Moment	moment(MinData(isnan(MinData)~=1),3);	3rd Moment
11	4th Central Moment	moment(MinData(isnan(MinData)~=1),4);	4th Moment
11	Number of Peaks	length(findpeaks(MinData ,'Threshold',1e-4,'MinPeakHeight', mean(MinData) + (max(MinData)-min(MinData))/4));	NumPeaks
11	Number of Prominent Peaks	length(findpeaks(MinData ,'Threshold',1e-6,'MinPeakProminence', (max(MinData)-min(MinData))/4));	NumOfPromPeaks
11	entropy	entropy(MinData);	Entropy
11	Number of Zero-Crossings	C = midcross(MinData(isnan(MinData)~=1),sampfreq); length(C);	ZeroCrossNumb
11	Mean Time between adjacent Zero-Crossings	if size(C,1) < 2; 60; else; mean(diff(C)); end	ZeroCrossMean
11	Median Time between adjacent Zero-Crossings	if size(C,1) < 2; 60; else; median(diff(C)); end	ZeroCrossMedian
11	SD of the Time between adjacent Zero-Crossings	if size(C,1) < 2; 0; else; std(diff(C)); end	ZeroCrossSD
11	Number of Median-Crossings	zci = @(MinData) find(MinData(:).*circshift(MinData(:), [-1 0]) <= 0); C = zci(MinData); length(C);	MidCrossNumb
11	Mean Time between adjacent Median-Crossings	if size(C,1) < 2; 60; else; mean(diff(C)); end	MidCrossMean
11	Median Time between adjacent Median-Crossings	if size(C,1) < 2; 60; else; median(diff(C)); end	MidCrossMedian
11	SD of Time between adjacent MedianCrossings	if size(C,1) < 2; 0; else; std(diff(C)); end	MidCrossSD
3	Dynamic Time Warping (DTW) between Axes	dtw(MinData(:,1), MinData(:,2)); % for x-y, (:,1) and (:,3) for x-z, (:,2) and (:,3) for y-z	DTW
3	DTW between Signal Changes from Frame to Frame	dtw(diff(MinData(:,1)), diff(MinData(:,2))); % for x-y, (:,1) and (:,3) for x-z, (:,2) and (:,3) for y-z	DTW 1st Derivate
3	Covariance between axes	CovTemp = nancov(MinData(:,1:3)); CovTemp(1,2) % for x-y; CovTemp(1,3) % for x-z; CovTemp(2,3) % for y-z;	Covariance between
3	Correlation between axes	corr(MinData(:,1),MinData(:,2)); % for x-y, (:,1) and (:,3) for x-z, (:,2) and (:,3) for y-z	Correlation between
11	SD of all non-overlapping 5 Seconds Mean	for i = 1:12; TempMean(i) = nanmean(MinData((i-1)*150+1:(i-1)*150+150,:)); end; std(TempMean)	std of 5sec Mean
11	SD of all non-overlapping 5 Seconds CV	for i = 1:12; TempStd(i) = nanstd(MinData((i-1)*150+1:(i-1)*150+150,:)); TempCV(i) = TempStd(i) ./ TempMean(i); end; std(TempCV)	std of 5sec CV
11	Mean Frequency *	MeanFreq = meanfreq(MinData,sampfreq);	MeanFreq
11	Power at Mean Frequency ±0.1Hz	L = [MeanFreq-0.1 MeanFreq+0.1]; if L(1) < 0; L(2) = L(2)+abs(L(1)); L(1) = 0; end; if L(2) > 15; L(1) = L(1) - (L(2)-15); L(2) = 15;end; bandpower(MinData,sampfreq,L);	MeanFreqPower
11	Median Frequency *	MedFreq = medfreq(MinData,sampfreq);	MedianFreq
11	Power at Median Frequency ±0.1Hz	L = [MedFreq-0.1 MedFreq+0.1]; if L(1) < 0; L(2) = L(2)+abs(L(1)); L(1) = 0; end; if L(2) > 15; L(1) = L(1) - (L(2)-15); L(2) = 15;end; bandpower(MinData,sampfreq,L);	MedianFreqPower
11	Mean Frequency between 0.3 to 3Hz *	MeanFreqLow = meanfreq(MinData,sampfreq,[0.3 3]);	MeanFreq 0.3-3Hz
11	Power at Mean Frequency ±0.1 Hz between 0.3 to 3Hz	L = [MeanFreqLow-0.1 MeanFreqLow+0.1]; if L(1) < 0; L(2) = L(2)+abs(L(1)); L(1) = 0; end;	MeanFreqPower 0.3-3Hz
11	Median Frequency between 0.3 to 3Hz *	MedFreqLow = medfreq(MinData,sampfreq,[0.3 3]);	MedianFreq 0.3-3Hz
11	Power at Median Frequency ±0.1Hz between 0.3 to 3 Hz	L = [MedFreqLow-0.1 MedFreqLow+0.1]; if L(1) < 0; L(2) = L(2)+abs(L(1)); L(1) = 0; end; if L(2) > 15; L(1) = L(1) - (L(2)-15); L(2) = 15;end; bandpower(MinData,sampfreq,L);	MedianFreqPower 0.3-3Hz
11	Total Signal Power	bandpower(MinData,sampfreq,[0 15]);	Total BandPower
11	Power below 0.3 Hz	bandpower(MinData,sampfreq,[0 0.3]);	BandPower <3Hz
11	Power between 0.3 and 3 Hz	bandpower(MinData,sampfreq,[0.3 3]);	BandPower 0.3-3Hz
11	Power above 3 Hz	bandpower(MinData,sampfreq,[3 15]);	BandPower >3Hz
11	Harmonic Power *	[~,harmpow,~] = thd(MinData,sampfreq); harmpow(1);	1st HarmPower
11	Harmonic Frequency *	[~,~,harmfreq] = thd(MinData,sampfreq); harmfreq(1);	1st HarmFreq

Appendix 2

```
%% KEY ELEMENTS OF THE MATLAB CODE USED IN THE STUDY
% 1) Describing the Feature Inclusion
% 2) Describing the Parameter Optimisation and Training


%% 1) Feature Inclusion
% The Feature Inclusion is done separately for each Placement, Signal Type,
% and GroundTruth (Posture, In-/Activity in Sitting, In-/Activity in
% Standing)
% The Feature inclusion needs 3 Inputs:
% 1: FeatureTable containing the filtered Features (column) with data of all Minutes (row).
% 2: GroundTruth containing the true label of each Minute
% 3: SubjectID containing the Subject information for each Minute

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%

% 1.1) Initialize CrossValidation:
cvType = 'kfold';
nPartitions = length(unique(SubjectID));
bags = 5;
% create partition object based on k-fold:
cvo = cvpartition(Response,cvType,nPartitions); clear cvType nPartitions
% Overwrite k-fold with SubjectID to get leave-one-out
cvo.Impl.indices = SubjectID;
% -> Works if MATLAB Source Code cvpartitionImpl.m is modified, see
%    C:\Program Files\matlab\R2018a\toolbox\stats\stats\+internal\+stats, and
%    change properties to public: (GetAccess = public, SetAccess = public!
% Design tree template
template = templateTree('MaxNumSplits', length(Response)-1);

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%

% 1.2) Stepwise Feature Inclusion
featnumb = 1 % initialise feature inclusion
stop = 'false' % stop if stop = 'true'
n = length(unique(Response)); % number of response possibilities
while strcmp(stop,'false')
   disp(['Searching Feature ',num2str(featnumb)])
   % Add one feature from FeatureTable
   for i = 1:size(FeatureTable,2)
      if featnumb == 1
         predictors = FeatureTable(:,i);
      else
         predictors = [PredictorsSelected FeatureTable(:,i)];
      end
      % Learning -> See Function Below (1.3)
      [BalancedSensSpec(i,fn)] = TrainTreeDirectValidation(predictors, GroundTruth, cvo, template, bags);
   end
   % Find the best
   [BalancedSensSpecIncluded(fn,1),ind] = max(BalancedSensSpec(:,fn));
   % Get its values and name
   PredictorsSelected(:,fn) = FeatureTable(:,ind);
   PredictorsSelected.Properties.VariableNames(fn) = FeatureTable.Properties.VariableNames{ind};
   % Remove it from FeatureTable
   FeatureTable(:,ind) = [];
```

```
    % Check whether the best indices is older than 10 additional Features!
    [~,indbest] = max(BalancedSensSpecIncluded(:,1));
    if indbest < fn-9 || fn > 100 % either for 10 Features not increased, or 100 Features included
        stop = 'true';
    end
    fn = fn+1;
end;
disp('Feature Search Completed!')

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%

% 1.3) Learning Function:
function [BalancedSensSpec] = TrainTreeDirectValidation(predictors, GroundTruth, cvo, template, bags)
% Learning
CVEnsembleMdl = fitcensemble(...
    predictors, ...
    GroundTruth, ...
    'Method', 'Bag', ...
    'NumLearningCycles', bags, ...
    'Learners', template, ...
    'ClassNames', [unique(GroundTruth)], ... %);
    'CVPartition',cvo);
% Compute validation predictions
[validationPredictions, ~] = kfoldPredict(CVEnsembleMdl);
% Compute Contingency Table:
for i = 1:length(unique(GroundTruth))
    for j = 1:length(unique(GroundTruth))
        ContingencyTable(i,j) = sum(validationPredictions==j-1 & GroundTruth==i-1);
    end
end
% Compute Sensitivity
for j = 1:length(unique(GroundTruth))
    Sensitivity(1,j) = ContingencyTable(j,j) ./ sum(ContingencyTable(j,:));
end
% Compute Specificity
for i=1:length(unique(GroundTruth))
    ContingencyTableTemp = ContingencyTable;
    ContingencyTableTemp(i,:) = []; % remove the true behaviour (the row)
    Prediction = ContingencyTableTemp(:,i); % get the wrongly predicted behaviour (the column)
    ContingencyTableTemp(:,i) = [];
    Specificity(1,i) = sum(sum(ContingencyTableTemp)) ./ (sum(sum(ContingencyTableTemp))+sum(Prediction)); % true to
true+wrong
end
% Compute Balanced Sensitivity and Specificity
BalancedSensSpec = (sum(Sensitivity) + sum(Specificity))./ (2*length(unique(GroundTruth)));




%% 2) Hyperparameter Optimisation:
% the Optimisation uses the PredictorsSelected from Feature inclusion, as
% well as GroundTruth and SubjectID

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%

% 2.1) Search optimized Hyperparameters
```

```
for featnumb = 1:length(PredictorsSelected,2)
   OptimizedEnsemble = fitcensemble(PredictorsSelected(:,1:featnumb),
GroundTruth,'OptimizeHyperparameters','all','HyperparameterOptimizationOptions',struct('CVpartition',cvo,'UseParallel',true,'V
erbose',0,'ShowPlots',false));
   ModelArchitecture = OptimizedEnsemble.HyperparameterOptimizationResults.XAtMinObjective

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%

   % 2.2) Design Tree with optimized Hyperparameters
   LearnerMethod = cellstr(ModelArchitecture.Method(featnumb));
   NumLearnCycle = ModelArchitecture.NumLearningCycles(featnumb);
   MinLeafSize = ModelArchitecture.MinLeafSize(featnumb);
   MaxNumSplits = ModelArchitecture.MaxNumSplits(featnumb);
   SplitCriterion = char(cellstr(ModelArchitecture.SplitCriterion(featnumb)));
   % If the bag method was selected
   if strcmp(LearnerMethod{1},'Bag')
      LearnRate = NaN;
      NumVariablesToSample = ModelArchitecture.NumVariablesToSample(featnumb);
      % Create Tree Template:
      template = templateTree('MaxNumSplits', MaxNumSplits, ...
         'MinLeafSize', MinLeafSize, ...
         'NumVariablesToSample',NumVariablesToSample, ...
         'SplitCriterion',SplitCriterion);
   % if there is no split criterion defined (e.g. GentleBoost)
   elseif strcmp( SplitCriterion,'<undefined>')
      LearnRate = ModelArchitecture.LearnRate(featnumb);
      NumVariablesToSample = NaN;
      template = templateTree('MaxNumSplits', MaxNumSplits, ...
         'MinLeafSize', MinLeafSize);
      % Everything else
   else
      LearnRate = ModelArchitecture.LearnRate(featnumb);
      NumVariablesToSample = NaN;
      template = templateTree('MaxNumSplits', MaxNumSplits, ...
         'MinLeafSize', MinLeafSize, ...
         'SplitCriterion',SplitCriterion);
   end

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%

   % 2.3) Do the Learning -> See Function Below (2.4)
   [BalancedSensSpecOpt(fn,1)] = TrainTreeDirectValidationPARAMOPT(PredictorsSelected(:,1:featnumb), GroundTruth, cvo,
template, LearnerMethod, NumLearnCycle, LearnRate);
   OptimizedHyperparameters{featnumb,1:7} = ModelArchitecture;
end
% SAVE THE FINAL MODEL ARCHITECTURES (OptimizedHyperparameters) AND VALIDITIES (BalancedSensSpecOpt)

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%

% 2.4) LearningFunction:
function[BalancedSensSpecOpt] = TrainTreeDirectValidationPARAMOPT(predictors, GroundTruth, cvo, template,
LearnerMethod, NumLearnCycle, LearnRate)
% Train the Tree
if strcmp(LearnerMethod{1},'Bag')
CVEnsembleMdl = fitcensemble(...
   predictors, ...
   GroundTruth, ...
```

```
    'Method', LearnerMethod{1}, ...
    'NumLearningCycles', NumLearnCycle, ...
    'Learners', template, ...
    'ClassNames',[unique(GroundTruth)], ...
    'CVPartition',cvo);
else
   CVEnsembleMdl = fitcensemble(...
    predictors, ...
    GroundTruth, ...
    'Method', LearnerMethod{1}, ...
    'NumLearningCycles', NumLearnCycle, ...
    'Learners', template, ...
    'LearnRate',LearnRate,... % this is the difference
    'ClassNames', [unique(GroundTruth)], ...
    'CVPartition',cvo);
end
% Compute validation predictions
[ValidationPredictions, LikelihoodPredictions] = kfoldPredict(CVEnsembleMdl); % PREDICTION (:,1) AND no idea what the second
output is (contains 0.5)
% Compute Contingency Table:
for i = 1:length(unique(GroundTruth))
    for j = 1:length(unique(GroundTruth))
        ContingencyTable(i,j) = sum(ValidationPredictions==j-1 & GroundTruth==i-1);
    end
end
% Compute Sensitivity
for j = 1:length(unique(GroundTruth))
    Sensitivity(1,j) = ContingencyTable(j,j) ./ sum(ContingencyTable(j,:));
end
% Compute Specificity
for i=1:length(unique(GroundTruth))
    ContingencyTableTemp = ContingencyTable;
    ContingencyTableTemp(i,:) = [];
    Prediction = ContingencyTableTemp(:,i);
    ContingencyTableTemp(:,i) = [];
    Specificity(1,i) = sum(sum(ContingencyTableTemp)) ./ (sum(sum(ContingencyTableTemp))+sum(Prediction)); % true to
true+wrong
end
% Compute Balanced Sensitivity Specificity
BalancedSensSpecOpt = (sum(Sensitivity) + sum(Specificity))./(2*length(unique(GroundTruth)));
```

Appendix 3: Missclassification table for each ground truth behaviour and accelerometer placement. Indicated is the prediction for each ground truth behaviour in percentage of total minutes spent in the ground truth behaviour, separately for the accelerometer only as well as the best signal combination. The correctly identified behaviour is indicated in grey, the most often missclassifyed one is marked in bold.

Accelerometers

Ground Truth:	**Sedentary Behaviour** (569 minutes)					**Active Sitting** (174 minutes)					**Inactive Standing** (425 minutes)					**Active Standing** (175 minutes)					**Walking** (150 minutes)				
Prediction:	Sedentary Behaviour	Active Sitting	Inactive Standing	Active Standing	Walking	Sedentary Behaviour	Active Sitting	Inactive Standing	Active Standing	Walking	Sedentary Behaviour	Active Sitting	Inactive Standing	Active Standing	Walking	Sedentary Behaviour	Active Sitting	Inactive Standing	Active Standing	Walking	Sedentary Behaviour	Active Sitting	Inactive Standing	Active Standing	Walking
Waist	78.6	8.8	**11.8**	0.9	0.0	**24.1**	65.5	5.7	4.6	0.0	**15.5**	1.4	77.2	5.9	0.0	3.4	1.7	**23.4**	71.4	0.0	0.0	0.0	0.0	0.0	100.0
Thigh (right)	91.2	**6.9**	1.9	0.0	0.0	**32.2**	67.8	0.0	0.0	0.0	2.4	0.2	93.2	**4.2**	0.0	0.0	0.0	**31.4**	68.6	0.0	0.0	0.0	0.0	0.0	100.0
Thigh (left)	87.9	**8.6**	3.5	0.0	0.0	**37.9**	62.1	0.0	0.0	0.0	3.1	1.2	89.2	**6.6**	0.0	0.6	8.0	**21.7**	69.7	0.0	0.0	0.0	0.0	0.0	100.0
Wrist (right)	73.1	4.4	**19.7**	2.8	0.0	**24.7**	45.4	12.6	16.1	1.1	**49.4**	4.5	42.4	3.8	0.0	14.9	**20.6**	10.9	52.0	1.7	0.0	0.0	0.0	**3.3**	96.7
Wrist (left)	73.3	2.1	**22.8**	1.8	0.0	**26.4**	56.3	5.7	11.5	0.0	**41.4**	0.9	52.7	4.9	0.0	13.1	12.0	**14.3**	60.6	0.0	0.0	0.0	0.0	0.0	100.0
Sternum	80.1	2.5	**16.0**	1.4	0.0	**20.7**	62.6	1.7	14.9	0.0	**22.4**	2.4	72.7	2.6	0.0	9.1	12.6	**18.3**	60.0	0.0	0.0	0.0	0.0	0.0	100.0
Head	66.6	4.4	**27.6**	1.4	0.0	**24.1**	34.5	20.1	20.7	0.6	**45.4**	3.8	50.1	0.7	0.0	**14.9**	12.0	14.3	57.1	1.7	0.0	0.0	0.0	0.0	100.0
Shoulder (right)	73.6	3.2	**19.9**	3.2	0.2	**25.9**	56.9	4.0	13.2	0.0	**17.9**	0.9	72.2	8.7	0.2	12.0	**14.9**	11.4	61.7	0.0	0.0	0.0	0.0	**0.7**	99.3
Shoulder (left)	80.0	3.7	**15.6**	0.7	0.0	**22.4**	59.2	6.9	11.5	0.0	**20.2**	0.7	74.4	4.7	0.0	10.9	8.0	**16.0**	65.1	0.0	0.0	0.0	0.0	0.0	100.0
Upper Arm (right)	72.9	5.1	**19.0**	3.0	0.0	**19.5**	52.9	9.8	17.8	0.0	**31.5**	4.2	58.6	5.6	0.0	8.0	13.7	**18.3**	60.0	0.0	0.0	0.0	0.0	0.0	100.0
Upper Arm (left)	73.6	3.7	**18.6**	4.0	0.0	**21.3**	50.6	10.3	17.8	0.0	**38.8**	1.6	52.9	6.6	0.0	9.1	13.1	**14.9**	62.9	0.0	0.0	0.0	0.0	0.0	100.0
Shank (right)	91.6	**5.3**	3.0	0.2	0.0	**35.1**	59.2	5.2	0.6	0.0	**8.7**	1.2	82.8	7.3	0.0	3.4	1.1	**22.9**	72.6	0.0	0.0	0.0	0.0	0.0	100.0
Shank (left)	91.6	**5.1**	3.2	0.2	0.0	**44.3**	51.7	2.9	1.1	0.0	6.1	1.4	84.5	**8.0**	0.0	1.1	2.3	**30.9**	65.7	0.0	0.0	0.0	0.0	0.0	100.0
Foot (right)	81.4	2.8	**14.4**	1.2	0.2	**32.2**	37.4	24.7	5.7	0.0	**23.3**	1.4	69.2	6.1	0.0	5.7	7.4	**30.3**	56.6	0.0	0.0	0.0	**0.7**	0.0	99.3
Foot (left)	79.3	6.9	**12.1**	1.8	0.0	**39.1**	44.3	8.0	8.6	0.0	**22.8**	5.2	65.6	6.4	0.0	4.0	9.1	**26.3**	60.6	0.0	0.0	0.0	0.0	0.0	100.0

Best Signal Combination

Ground Truth:	**Sedentary Behaviour** (569 minutes)					**Active Sitting** (174 minutes)					**Inactive Standing** (425 minutes)					**Active Standing** (175 minutes)					**Walking** (150 minutes)				
Prediction:	Sedentary Behaviour	Active Sitting	Inactive Standing	Active Standing	Walking	Sedentary Behaviour	Active Sitting	Inactive Standing	Active Standing	Walking	Sedentary Behaviour	Active Sitting	Inactive Standing	Active Standing	Walking	Sedentary Behaviour	Active Sitting	Inactive Standing	Active Standing	Walking	Sedentary Behaviour	Active Sitting	Inactive Standing	Active Standing	Walking
Waist	87.7	4.7	**7.2**	0.4	0.0	**24.1**	65.5	5.7	4.6	0.0	**7.8**	0.5	86.4	5.4	0.0	3.4	1.7	**23.4**	71.4	0.0	0.0	0.0	0.0	0.0	100.0
Thigh (right)	91.2	**6.9**	1.9	0.0	0.0	**32.2**	67.8	0.0	0.0	0.0	2.4	0.2	93.2	**4.2**	0.0	0.0	0.0	**31.4**	68.6	0.0	0.0	0.0	0.0	0.0	100.0
Thigh (left)	90.7	**8.1**	1.2	0.0	0.0	**37.9**	62.1	0.0	0.0	0.0	0.0	0.2	93.9	**5.9**	0.0	0.6	8.0	**21.7**	69.7	0.0	0.0	0.0	0.0	0.0	100.0
Wrist (right)	73.1	4.4	**19.7**	2.8	0.0	**24.7**	45.4	12.6	16.1	1.1	**49.4**	4.5	42.4	3.8	0.0	14.9	**20.6**	10.9	52.0	1.7	0.0	0.0	0.0	**3.3**	96.7
Wrist (left)	73.3	2.1	**22.8**	1.8	0.0	**26.4**	56.3	5.7	11.5	0.0	**41.4**	0.9	52.7	4.9	0.0	13.1	12.0	**14.3**	60.6	0.0	0.0	0.0	0.0	0.0	100.0
Sternum	80.1	2.5	**16.0**	1.4	0.0	**20.7**	62.6	1.7	14.9	0.0	**22.4**	2.4	72.7	2.6	0.0	**9.7**	8.0	**9.1**	73.1	0.0	0.0	0.0	0.0	0.0	100.0
Head	78.4	6.0	**14.6**	1.1	0.0	**15.5**	55.7	9.8	**18.4**	0.6	**18.6**	1.2	74.4	5.9	0.0	**14.9**	12.0	14.3	57.1	1.7	0.0	0.0	0.0	0.0	100.0
Shoulder (right)	73.6	3.2	**19.9**	3.2	0.2	**25.9**	56.9	4.0	13.2	0.0	**17.9**	0.9	72.2	8.7	0.2	9.1	**4.6**	**18.9**	67.4	0.0	0.0	0.0	0.0	**0.7**	99.3
Shoulder (left)	87.3	4.7	**7.2**	0.7	0.0	**25.9**	68.4	1.1	4.6	0.0	**20.2**	0.7	74.4	4.7	0.0	10.9	8.0	**16.0**	65.1	0.0	0.0	0.0	0.0	0.0	100.0
Upper Arm (right)	72.9	5.1	**19.0**	3.0	0.0	**19.5**	52.9	9.8	17.8	0.0	**31.5**	4.2	58.6	5.6	0.0	8.0	13.7	**18.3**	60.0	0.0	0.0	0.0	0.0	0.0	100.0
Upper Arm (left)	73.6	3.7	**18.6**	4.0	0.0	**21.3**	50.6	10.3	17.8	0.0	**38.8**	1.6	52.9	6.6	0.0	9.1	13.1	**14.9**	62.9	0.0	0.0	0.0	0.0	0.0	100.0
Shank (right)	95.6	**3.3**	0.9	0.2	0.0	**31.0**	65.5	1.7	1.7	0.0	**8.7**	1.2	82.8	7.3	0.0	3.4	1.1	**22.9**	72.6	0.0	0.0	0.0	0.0	0.0	100.0
Shank (left)	91.6	**5.1**	3.2	0.2	0.0	**33.9**	64.9	1.1	0.0	0.0	6.1	1.4	84.5	**8.0**	0.0	1.1	2.3	**30.9**	65.7	0.0	0.0	0.0	0.0	0.0	100.0
Foot (right)	81.4	2.8	**14.4**	1.2	0.2	**32.2**	37.4	24.7	5.7	0.0	**23.3**	1.4	69.2	6.1	0.0	5.7	7.4	**30.3**	56.6	0.0	0.0	0.0	**0.7**	0.0	99.3
Foot (left)	88.6	4.4	**6.5**	0.5	0.0	**39.1**	44.3	8.0	8.6	0.0	**22.8**	5.2	65.6	6.4	0.0	4.0	9.1	**26.3**	60.6	0.0	0.0	0.0	0.0	0.0	100.0

Appendix 4: Selected Features of the best model for each sensor placement. In case the addition of the gyroscope and/or magnetometer increased the accuarcy, the sensor type on which a particular feature is calculated is indicated with A (accelerometer), G (gyroscope), and M (magnetometer). The code on how to calculate the features is shown in Appendix 1.

Waist (Accelerometer + Gyroscope + Magnetometer)

Posture	Activity in Sitting	Activity in Standing
A: BandPower VM	G: 5th Percentile Z	G: 25th Percentile VM_filt
G: ZeroCrossMedian_X	A: BandPower 0.3-3Hz X_filt	M: iqr VM
M: 1st Percentile VM_filt	A: abs SignalChange X_filt	M: NumPromPeaks VM
A: Skewness VM	G: DTW 1st Derivate XZ	G: 75th Percentile Z_filt
G: iqr Z	M: MedianFreq 0.3-3Hz VM	
A: 99th Percentile VM	G: BandPower >3Hz X	
G: 75th Percentile Y	G: 25th Percentile X_filt	
A: BandPower >3Hz X	A: Entropy Y_filt	
G: Lag1Autocorr VM	A: DTW 1st Derivate YZ	
G: Lag1Autocorr X	M: BandPower <3Hz X_Angle	
G: Mean VM	A: abs SignalChange X_Angle	
G: 75th Percentile Z	M: BandPower 0.3-3Hz Z	
G: Kurtosis X_Angle	A: BandPower 0.3-3Hz X	
M: max VM	M: MeanFreq 0.3-3Hz X_Angle	
M: 50th Percentile Z_Angle	G: Lag1Autocorr Y	
G: NumPeaks X_Angle	M: NumPeaks VM	
A: DTW 1st Derivate XY		
A: BandPower 0.3-3Hz X		
A: min Z		
G: NumPromPeaks X_Angle		
M: std VM		
A: BandPower 0.3-3Hz VM		

Thigh right (Accelerometer)

Posture	Activity in Sitting	Activity in Standing
90th Percentile X	abs SignalChange Z_filt	abs SignalChange X_Angle
90th Percentile X_Angle	MedianFreq 0.3-3Hz Z_filt	Range Z_filt
BandPower >3Hz Y	std Z	
	Entropy Z_Angle	
	MidCrossMedian VM_filt	

Thigh left (Accelerometer + Gyroscope)

Posture	Activity in Sitting	Activity in Standing
A: 99th Percentile X	G: Entropy X_Angle	G: 75th Percentile X
A: BandPower Y	G: CoeffVariation Y_filt	
A: BandPower VM_filt		
A: BandPower <3Hz Y		
A: MeanFreqPower_Y_filt		

Wrist right (Accelerometer)

90th Percentile X	abs SignalChange VM_filt	95th Percentile VM_filt
5th Percentile VM_filt	MedianFreqPower Z	MeanFreq 0.3-3Hz Z
75th Percentile X	MeanFreq 0.3-3Hz X	75th Percentile VM
Covariance between XY	5th Percentile VM_filt	90th Percentile VM
MedianFreq 0.3-3Hz X	Correlation between XY	
MeanFreqPower_Z	MedianFreq VM	
	Mean Z_Angle	
	BandPower 0.3-3Hz Y	

Wrist left (Accelerometer)

Posture	Activity in Sitting	Activity in Standing
75th Percentile X_Angle	abs SignalChange VM_filt	95th Percentile VM
Lag1secAutocor_Z_filt		90th Percentile VM_filt
MedianFreq 0.3-3Hz Z		3rd Moment Y_Angle
Range X_filt		MeanFreq 0.3-3Hz Z_filt
MeanFreqPower_VM_filt		

Sternum (Accelerometer)

Posture	Activity in Sitting	Activity in Standing
NumPromPeaks VM_filt	abs SignalChange Z_filt	25th Percentile VM
std of 5sec CV VM	Entropy Z	MeanFreqPower 0.3-3Hz Y_Angle
1st HarmFreq VM	std Y	MeanFreqPower 0.3-3Hz Z
iqr VM	abs SignalChange X	ZeroCrossNumb Y
MeanFreqPower 0.3-3Hz X	Range Y	Range Y
MeanFreq VM	BandPower 0.3-3Hz VM	
90th Percentile Z	std of 5sec CV VM_filt	
3rd Moment VM		
BandPower >3Hz Z		
MedianFreqPower 0.3-3Hz X		
CoeffVariation VM		
NumPromPeaks VM		
50th Percentile Z		
DTW 1st Derivate XY		
Mean Z_Angle		
75th Percentile Z_filt		
3rd Moment X		
MedianFreq 0.3-3Hz VM		
4th Moment VM		
MidCrossMean VM		
95th Percentile Z		
MidCrossMedian VM		
75th Percentile Z		
50th Percentile Z_filt		
Lag1Autocorr Y		
Kurtosis VM		
MedianFreq 0.3-3Hz Z		

Head (Accelerometer + Gyroscope + Magnetometer)

Posture	Activity in Sitting	Activity in Standing
M: 90th Percentile VM	G: iqr Z	G: iqr Z
M: 5th Percentile VM	G: Lag1Autocorr Y_Angle	G: Lag1Autocorr Y
G: Mean Y	M: max Z_Angle	A: 99th Percentile VM
A: Range VM	A: MeanFreq Z	M: min VM
M: MedianFreq X_filt	A: abs SignalChange X_Angle	
A: Lag1secAutocor_VM	G: Mean VM_filt	
G: DTW 1st Derivate YZ	M: 99th Percentile Z_filt	
M: 1st Percentile VM	M: 1st HarmPower VM_filt	
	G: zdtwXZ	
	A: 3rd Moment VM_filt	
	A: MedianFreqPower VM_filt	
	A: 75th Percentile VM_filt	
	G: SUBEPIstdMean Y_filt	
	A: iqr Z	
	M: DTW 1st Derivate XZ	
	A: Range Z	

Shoulder right (Accelerometer)

Posture	Activity in Sitting	Activity in Standing
NumPromPeaks VM_filt	abs SignalChange Y_filt	95th Percentile VM_filt
10th Percentile VM_filt	MedianFreqPower 0.3-3Hz X_filt	MedianFreq X_Angle
std of 5sec CV VM		iqr Y_filt
MeanFreq Z		abs SignalChange Z
BandPower 0.3-3Hz Z		90th Percentile X_filt
Range VM_filt		std VM
25th Percentile VM		ZeroCrossNumb X_filt
BandPower 0.3-3Hz VM_filt		DTW 1st Derivate XY
1st HarmFreq VM		BandPower >3Hz Y
MeanFreq 0.3-3Hz VM		3rd Moment X_filt
		BandPower 0.3-3Hz Y
		DTW 1st Derivate XZ
		ZeroCrossNumb X_Angle
		min Y
		abs SignalChange VM_filt
		abs SignalChange Y_filt
		90th Percentile X_Angle

Shoulder left (Accelerometer + Gyroscope + Magnetometer)

Posture	Activity in Sitting	Activity in Standing
M: min VM	M: DTW 1st Derivate XY	G: 25th Percentile Z
G: MeanFreq Z	A: std X	M: BandPower Z_filt
A: MeanFreq VM_filt	M: MeanFreqPower 0.3-3Hz X_filt	G: 90th Percentile X
G: abs SignalChange Y	G: 99th Percentile Z	A: MedianFreqPower 0.3-3Hz X_filt
G: MedianFreq 0.3-3Hz Y	G: 10th Percentile Z_Angle	M: MeanFreq Z_filt
A: 1st Percentile Z_filt	G: 95th Percentile VM	A: Entropy X
G: Lag1Autocorr X_Angle	A: Entropy Y_Angle	
A: 5th Percentile VM_filt	A: Correlation between YZ	
A: std of 5sec CV VM_filt	A: CoeffVariation VM	
G: MeanFreqPower 0.3-3Hz Z	M: MeanFreq Y_Angle	
G: DTW 1st Derivate YZ	G: 90th Percentile Y	
M: Range Z		
M: 4th Moment VM_filt		
A: Skewness VM		
M: 95th Percentile VM		
G: ZeroCrossNumb Y		
A: 10th Percentile Z_Angle		

Upper Arm right (Accelerometer)

Posture	Activity in Sitting	Activity in Standing
DTW 1st Derivate XZ	5th Percentile VM_filt	abs SignalChange X_Angle
MedianFreq 0.3-3Hz Y	5th Percentile VM	zdtwXY
99th Percentile X	BandPower 0.3-3Hz X_Angle	abs SignalChange Y_filt
MedianFreq 0.3-3Hz X_Angle	BandPower 0.3-3Hz X	
BandPower >3Hz X	MedianFreqPower 0.3-3Hz VM_filt	
MeanFreq 0.3-3Hz Z	NumPromPeaks VM	
10th Percentile VM	BandPower 0.3-3Hz VM_filt	
BandPower VM		
MedianFreq 0.3-3Hz X		
Skewness Y		
MedianFreqPower VM_filt		
MedianFreqPower 0.3-3Hz VM		
min Z_Angle		
MedianFreq 0.3-3Hz X_filt		
iqr X		
Correlation between XY		
1st Percentile VM		
BandPower >3Hz VM		
zdtwYZ		
99th Percentile X_filt		
MedianFreq 0.3-3Hz VM		
iqr VM_filt		
MeanFreq 0.3-3Hz VM_filt		
MeanFreq 0.3-3Hz VM		
99th Percentile VM		
50th Percentile VM		
1st Percentile VM_filt		
3rd Moment Z		
MedianFreq VM		
50th Percentile VM_filt		
max Y_Angle		
MeanFreqPower 0.3-3Hz X		
BandPower >3Hz VM_filt		
1st HarmPower VM		
99th Percentile X_Angle		
Mean VM		
90th Percentile VM		

Upper Arm left (Accelerometer)

Posture	Activity in Sitting	Activity in Standing
90th Percentile X	abs SignalChange X_Angle	MeanFreq VM_filt
10th Percentile X	MidCrossNumb_Y	std Z
abs SignalChange Z	DTW 1st Derivate YZ	iqr VM
3rd Moment X	10th Percentile X_filt	abs SignalChange Y_Angle
MeanFreq 0.3-3Hz VM_filt	BandPower 0.3-3Hz Z	BandPower 0.3-3Hz VM
90th Percentile VM	iqr VM_filt	MeanFreqPower 0.3-3Hz X
DTW 1st Derivate YZ	BandPower 0.3-3Hz X	
MedianFreq 0.3-3Hz Y	MeanFreqPower 0.3-3Hz X	
99th Percentile X	Kurtosis Z	
4th Moment VM	4th Moment Z	
MeanFreq 0.3-3Hz X	std Z_filt	
5th Percentile X_filt	BandPower >3Hz VM	
BandPower <3Hz VM	MeanFreqPower 0.3-3Hz Y	
5th Percentile VM	MeanFreq X	
BandPower X_Angle	MedianFreqPower 0.3-3Hz X_Angle	
std of 5sec CV Z	MeanFreqPower 0.3-3Hz Z_Angle	
25th Percentile VM	iqr Z_Angle	
std of 5sec CV X_Angle	BandPower 0.3-3Hz Y	
MeanFreq 0.3-3Hz Y	BandPower >3Hz X	

Shank right (Accelerometer + Gyroscope)

Posture	Activity in Sitting	Activity in Standing
G: MeanFreqPower 0.3-3Hz Y_Angle	G: ZeroCrossNumb_Z	G: 90th Percentile X
G: 95th Percentile X_Angle	G: MidCrossMedian Y_Angle	A: Kurtosis X_filt
G: 90th Percentile Y	G: MedianFreq X_filt	A: 99th Percentile VM
G: ZeroCrossSD Z	A: 4th Moment Z_Angle	A: ZeroCrossSD Z
G: 95th Percentile Z	A: Range X_Angle	G: 50th Percentile Z_Angle
A: Covariance between YZ	G: 5th Percentile Y_filt	A: 1st Percentile VM
A: Skewness VM_filt	A: iqr Z_filt	A: MeanFreqPower 0.3-3Hz Y_Angle
G: 75th Percentile VM		A: NumPeaks Y
G: 50th Percentile Y		A: 1st HarmFreq Z
G: iqr Y_filt		A: 95th Percentile VM
A: min VM		
A: BandPower 0.3-3Hz VM_filt		
G: max X		
G: 1st Percentile VM		
G: Correlation betweenYZ		
G: 95th Percentile Z_filt		
G: 25th Percentile Y_filt		
A: MeanFreq 0.3-3Hz Z		
G: ZeroCrossSD Y		
G: std Y_Angle		
G: 3rd Moment_Z_Angle		
G: Mean VM		
G: 10th Percentile VM		

Shank left (Accelerometer)

Posture	Activity in Sitting	Activity in Standing
max VM_filt	abs SignalChange X_Angle	ZeroCrossNumb Y
min VM	BandPower 0.3-3Hz X_Angle	25th Percentile VM
MeanFreq 0.3-3Hz Y	Lag1Autocorr X	CoeffVariation VM
99th Percentile X	Lag1Autocorr Z	MeanFreq 0.3-3Hz Z
3rd Moment VM_filt	BandPower 0.3-3Hz X_filt	MedianFreq Y_Angle
90th Percentile VM	5th Percentile Y_Angle	MedianFreq 0.3-3Hz Y_Angle
Correlation between YZ		MidCrossMean Y_Angle
abs SignalChange X_Angle		
1st HarmFreq Z		
abs SignalChange Z_filt		
Lag1Autocorr VM_filt		
DTW 1st Derivate YZ		
4th Moment VM_filt		
1st Percentile VM		
50th Percentile X		
BandPower >3Hz VM		

Foot right (Accelerometer)

Posture	Activity in Sitting	Activity in Standing
NumPeaks X_filt	ZeroCrossMedian_Y	Entropy Y
NumPeaks VM_filt	Entropy X_Angle	MedianFreq Z_Angle
MedianFreqPower Z_Angle	iqr X_filt	Lag1secAutocor_Z_Angle
MeanFreq 0.3-3Hz Y	5th Percentile Y_filt	abs SignalChange Z_filt
BandPower 0.3-3Hz X_filt	iqr Y	MeanFreqPower 0.3-3Hz Y_Angle
90th Percentile X		99th Percentile X_filt
MeanFreqPower 0.3-3Hz VM_filt		Range Z_filt
MedianFreqPower 0.3-3Hz VM_filt		abs SignalChange X_filt
99th Percentile VM		CoeffVariation VM
BandPower >3Hz Z		Lag1secAutocor_Z_filt
Range Y		90th Percentile Y_Angle
ZeroCrossNumb X		99th Percentile VM
3rd Moment X_filt		NumPromPeaks X_filt
Range Y_Angle		CoeffVariation Z_filt
99th Percentile VM_filt		Mean VM_filt
BandPower >3Hz X_filt		
99th Percentile Z_Angle		
max Z_filt		

Foot left (Accelerometer + Gyroscope + Magnetometer)

Posture	Activity in Sitting	Activity in Standing
M: max VM_filt	G: ZeroCrossNumb Z_filt	G: NumPeaks VM_filt
A: 90th Percentile VM_filt	G: 75th Percentile Z_Angle	M: max X_filt
G: 1st Percentile VM_filt	A: CoeffVariation Z	A: 5th Percentile X
M: 10th Percentile X_filt	A: max Z_filt	M: NumPromPeaks Y_Angle
A: MedianFreq 0.3-3Hz Y	G: 90th Percentile Y_Angle	M: 1st HarmPower Z
M: BandPower <3Hz VM_filt	G: 99th Percentile X_Angle	M: BandPower 0.3-3Hz X_Angle
G: abs SignalChange Y_filt	A: 10th Percentile X	A: 1st Percentile Y
G: ZeroCrossMedian_X		M: 25th Percentile VM_filt
G: 1st HarmFreq Z		G: Correlation between XY
A: BandPower >3Hz VM_filt		M: abs SignalChange Y_filt
A: Skewness X_filt		G: 95th Percentile Z
M: NumPeaks Z_Angle		

Appendix 5: Accuracy of sensor placement and signal type (accelerometer only, and best signal combination as shown in table 3) to classify desk based activities into posture and physical in-/activity level in sitting and standing (inactive: ≤1.5 MET, active: >1.5 MET), separated by office task for each behaviour. Sedentary Behaviour is equal to inactive sitting. The number of subjects in each behaviour-task combination is indicated at the bottom. Note that in some behaviour-task combinations, the number of subjects is quite low (e.g. 5 for SB in Sorting) or even no subject showed a particular behaviour in a given office task (Active Standing in Mouse)

Sedentary Behaviour

Task	Mouse			Keyboard			Deskwork			Sorting		
	Accelerometer	Best Signal Combination		Accelerometer	Best Signal Combination		Accelerometer	Best Signal Combination		Accelerometer	Best Signal Combination	
Sensor	Accuracy	Accuracy	Type	Accuracy	Accuracy	Type	Accuracy	Accuracy	Type	Accuracy	Accuracy	Type
Waist	90.0 [80.0 - 100.0]	95.0 [80.0 - 100.0]	+ G + M	80.0 [75.0 - 90.0]*	100.0 [90.0 - 100.0]	+ G + M	85.0 [60.0 - 100.0]	90.0 [80.0 - 100.0]	+ G + M	100.0 [96.3 - 100.0]	100.0 [100.0 - 100.0]	+ G + M
Thigh (right)	**100.0 [100.0 - 100.0]**			**100.0 [100.0 - 100.0]**			90.0 [80.0 - 100.0]			100.0 [90.0 - 100.0]		
Thigh (left)	90.0 [90.0 - 100.0]	100.0 [100.0 - 100.0]	+ G	100.0 [90.0 - 100.0]	100.0 [100.0 - 100.0]	+ G	**100.0 [82.6 - 100.0]**	90.0 [78.2 - 100.0]	+ G	100.0 [90.0 - 100.0]	100.0 [100.0 - 100.0]	+ G
Wrist (right)	60.0 [50.0 - 70.0]*			62.5 [48.2 - 68.6]*			60.0 [50.0 - 80.0]*			100.0 [90.0 - 100.0]		
Wrist (left)	70.0 [60.0 - 73.7]*			55.0 [50.0 - 70.0]*			60.0 [50.0 - 70.0]*			100.0 [96.3 - 100.0]		
Sternum	70.0 [60.0 - 90.0]*			85.0 [75.0 - 90.0]*			80.0 [70.0 - 90.0]			100.0 [90.0 - 100.0]		
Head	60.0 [50.0 - 70.0]*	100.0 [92.6 - 100.0]	+ G + M	55.0 [50.0 - 65.0]*	75.0 [68.2 - 75.0]*	+ G + M	60.0 [46.3 - 70.0]*	80.0 [70.0 - 90.0]	+ G + M	100.0 [90.0 - 100.0]	100.0 [100.0 - 100.0]	+ G + M
Shoulder (right)	80.0 [60.0 - 90.0]*			77.5 [63.2 - 90.0]*			80.0 [60.0 - 90.0]*			100.0 [100.0 - 100.0]		
Shoulder (left)	80.0 [66.3 - 90.0]*	85.0 [70.0 - 93.7]*	+ G + M	77.5 [68.2 - 81.8]*	80.0 [73.2 - 95.0]*	+ G + M	80.0 [70.0 - 90.0]	90.0 [80.0 - 100.0]	+ G + M	100.0 [90.0 - 100.0]	100.0 [90.0 - 100.0]	+ G + M
Upper Arm (right)	70.0 [60.0 - 80.0]*			67.5 [60.0 - 80.0]*			70.0 [60.0 - 76.8]*			100.0 [100.0 - 100.0]		
Upper Arm (left)	60.0 [60.0 - 70.0]*			70.0 [60.0 - 71.8]*			60.0 [50.0 - 73.7]*			100.0 [100.0 - 100.0]		
Shank (right)	100.0 [90.0 - 100.0]	100.0 [100.0 - 100.0]	+ G	95.0 [90.0 - 100.0]	100.0 [93.2 - 100.0]	+ G	90.0 [80.0 - 100.0]	100.0 [90.0 - 100.0]	+ G	90.0 [80.0 - 100.0]	100.0 [90.0 - 100.0]	+ G
Shank (left)	100.0 [90.0 - 100.0]			95.0 [83.2 - 100.0]			95.0 [80.0 - 100.0]			90.0 [86.3 - 100.0]		
Foot (right)	75.0 [70.0 - 90.0]*			80.0 [68.2 - 86.8]*			85.0 [76.3 - 93.7]			90.0 [86.3 - 100.0]		
Foot (left)	80.0 [60.0 - 90.0]*	85.0 [70.0 - 100.0]*	+ G + M	80.0 [60.0 - 90.0]*	85.0 [80.0 - 95.0]*	+ G + M	80.0 [70.0 - 90.0]	90.0 [70.0 - 100.0]	+ G + M	90.0 [80.0 - 100.0]	95.0 [90.0 - 100.0]	+ G + M
# of Subjects	27			28			23			5		

Active Sitting

Task	Mouse			Keyboard			Deskwork			Sorting		
	Accelerometer	Best Signal Combination		Accelerometer	Best Signal Combination		Accelerometer	Best Signal Combination		Accelerometer	Best Signal Combination	
Sensor	Accuracy	Accuracy	Type	Accuracy	Accuracy	Type	Accuracy	Accuracy	Type	Accuracy	Accuracy	Type
Waist	100.0 [100.0 - 100.0]			100.0 [93.3 - 100.0]			86.7 [76.3 - 100.0]			90.0 [90.0 - 100.0]		
Thigh (right)	100.0 [100.0 - 100.0]			100.0 [100.0 - 100.0]			90.0 [80.0 - 100.0]			**100.0 [90.0 - 100.0]**		
Thigh (left)	100.0 [100.0 - 100.0]			100.0 [93.3 - 100.0]			100.0 [82.6 - 100.0]			100.0 [90.0 - 100.0]		
Wrist (right)	**100.0 [100.0 - 100.0]**			100.0 [100.0 - 100.0]			95.0 [80.0 - 100.0]			70.0 [56.3 - 80.0]*		
Wrist (left)	100.0 [100.0 - 100.0]			100.0 [100.0 - 100.0]			100.0 [100.0 - 100.0]			80.0 [70.0 - 93.7]		
Sternum	100.0 [100.0 - 100.0]			100.0 [100.0 - 100.0]			95.0 [90.0 - 100.0]			80.0 [76.3 - 90.0]		
Head	100.0 [100.0 - 100.0]	100.0 [100.0 - 100.0]	+ G	100.0 [100.0 - 100.0]	100.0 [100.0 - 100.0]	+ G	90.0 [66.3 - 100.0]	95.0 [80.0 - 100.0]	+ G	70.0 [60.0 - 83.7]*	80.0 [66.3 - 90.0]	+ G
Shoulder (right)	100.0 [100.0 - 100.0]			100.0 [100.0 - 100.0]			100.0 [76.3 - 100.0]			80.0 [70.0 - 90.0]*		
Shoulder (left)	100.0 [100.0 - 100.0]	100.0 [100.0 - 100.0]	+ G + M	**100.0 [100.0 - 100.0]**	100.0 [100.0 - 100.0]	+ G + M	**100.0 [90.0 - 100.0]**	100.0 [80.0 - 100.0]	+ G + M	85.0 [70.0 - 90.0]*	100.0 [90.0 - 100.0]	+ G + M
Upper Arm (right)	100.0 [100.0 - 100.0]			100.0 [100.0 - 100.0]			90.0 [76.3 - 100.0]			80.0 [66.3 - 80.0]*		
Upper Arm (left)	100.0 [100.0 - 100.0]			100.0 [100.0 - 100.0]			100.0 [90.0 - 100.0]			80.0 [70.0 - 90.0]*		
Shank (right)	100.0 [100.0 - 100.0]	100.0 [100.0 - 100.0]	+ G	100.0 [100.0 - 100.0]	100.0 [100.0 - 100.0]	+ G	100.0 [80.0 - 100.0]	100.0 [90.0 - 100.0]	+ G	90.0 [80.0 - 100.0]	100.0 [90.0 - 100.0]	+ G
Shank (left)	100.0 [100.0 - 100.0]	100.0 [100.0 - 100.0]	+ M	100.0 [100.0 - 100.0]	100.0 [100.0 - 100.0]	+ M	95.0 [90.0 - 100.0]	100.0 [86.3 - 100.0]	+ M	90.0 [70.0 - 100.0]	100.0 [86.3 - 100.0]	+ M
Foot (right)	100.0 [100.0 - 100.0]			100.0 [100.0 - 100.0]			100.0 [80.0 - 100.0]			75.0 [66.3 - 90.0]		
Foot (left)	100.0 [100.0 - 100.0]			100.0 [93.3 - 100.0]*			90.0 [76.3 - 100.0]*			80.0 [70.0 - 83.7]*		
# of Subjects	3			2			7			25		

Inactive Standing

Task	Mouse			Keyboard			Deskwork			Sorting		
	Accelerometer	Best Signal Combination		Accelerometer	Best Signal Combination		Accelerometer	Best Signal Combination		Accelerometer	Best Signal Combination	
Sensor	Accuracy	Accuracy	Type	Accuracy	Accuracy	Type	Accuracy	Accuracy	Type	Accuracy	Accuracy	Type
Waist	90.0 [80.0 - 100.0]*	100.0 [80.0 - 100.0]	+ G + M	85.0 [75.0 - 91.2]*	100.0 [90.0 - 100.0]	+ G + M	90.0 [70.0 - 100.0]*	95.0 [90.0 - 100.0]	+ G + M	100.0 [90.0 - 100.0]	100.0 [90.0 - 100.0]	+ G + M
Thigh (right)	**100.0 [100.0 - 100.0]**			**100.0 [100.0 - 100.0]**			100.0 [96.3 - 100.0]			**100.0 [100.0 - 100.0]**		
Thigh (left)	95.0 [90.0 - 100.0]	100.0 [100.0 - 100.0]	+ G	100.0 [100.0 - 100.0]	100.0 [100.0 - 100.0]	+ G	**100.0 [90.0 - 100.0]**	100.0 [100.0 - 100.0]	+ G	100.0 [90.0 - 100.0]	100.0 [100.0 - 100.0]	+ G
Wrist (right)	60.0 [50.0 - 70.0]*			60.0 [45.0 - 65.0]*			70.0 [50.0 - 80.0]*			100.0 [87.5 - 100.0]		
Wrist (left)	70.0 [60.0 - 70.0]*			60.0 [50.0 - 73.7]*			70.0 [50.0 - 73.7]*			100.0 [100.0 - 100.0]		
Sternum	70.0 [60.0 - 90.0]*			82.5 [75.0 - 90.0]*			80.0 [70.0 - 90.0]			100.0 [90.0 - 100.0]		
Head	60.0 [50.0 - 70.0]*	100.0 [92.6 - 100.0]	+ G + M	55.0 [50.0 - 65.0]*	75.0 [63.2 - 76.8]*	+ G + M	60.0 [50.0 - 60.9]*	90.0 [76.3 - 100.0]	+ G + M	100.0 [86.3 - 100.0]	100.0 [90.0 - 100.0]	+ G + M
Shoulder (right)	80.0 [60.0 - 90.0]*			80.0 [70.0 - 91.2]			80.0 [66.3 - 90.0]			100.0 [100.0 - 100.0]		
Shoulder (left)	80.0 [60.0 - 90.0]*			80.0 [70.0 - 86.8]*			85.0 [70.0 - 90.0]			100.0 [100.0 - 100.0]		
Upper Arm (right)	70.0 [60.0 - 80.0]*			68.3 [60.0 - 81.6]*			70.0 [60.0 - 76.8]*			100.0 [86.3 - 100.0]		
Upper Arm (left)	60.0 [50.0 - 73.7]*			70.0 [60.0 - 75.0]*			70.0 [60.0 - 80.0]*			100.0 [100.0 - 100.0]		
Shank (right)	100.0 [96.3 - 100.0]			95.0 [90.0 - 100.0]			90.0 [76.3 - 100.0]			100.0 [100.0 - 100.0]		
Shank (left)	100.0 [90.0 - 100.0]			100.0 [94.4 - 100.0]			90.0 [80.0 - 100.0]			90.0 [76.3 - 100.0]*		
Foot (right)	80.0 [70.0 - 90.0]*			75.0 [63.2 - 85.0]*			90.0 [70.0 - 93.7]			80.0 [70.0 - 93.7]*		
Foot (left)	80.0 [60.0 - 83.7]*			74.7 [66.7 - 90.0]*			80.0 [76.3 - 90.0]			90.0 [76.3 - 100.0]		
# of Subjects	30			27			23			5		

Active Standing

Task	Mouse			Keyboard			Deskwork			Sorting		
	Accelerometer	Best Signal Combination		Accelerometer	Best Signal Combination		Accelerometer	Best Signal Combination		Accelerometer	Best Signal Combination	
Sensor	Accuracy	Accuracy	Type	Accuracy	Accuracy	Type	Accuracy	Accuracy	Type	Accuracy	Accuracy	Type
Waist	100.0 [100.0 - 100.0]			100.0 [100.0 - 100.0]			100.0 [90.0 - 100.0]			90.0 [90.0 - 100.0]		
Thigh (right)	**100.0 [100.0 - 100.0]**			100.0 [100.0 - 100.0]			100.0 [96.3 - 100.0]			**100.0 [100.0 - 100.0]**		
Thigh (left)	100.0 [100.0 - 100.0]			100.0 [100.0 - 100.0]			100.0 [90.0 - 100.0]			100.0 [90.0 - 100.0]		
Wrist (right)	100.0 [100.0 - 100.0]			100.0 [100.0 - 100.0]			95.0 [90.0 - 100.0]			70.0 [60.0 - 90.0]*		
Wrist (left)	100.0 [100.0 - 100.0]			100.0 [100.0 - 100.0]			100.0 [90.0 - 100.0]			80.0 [70.0 - 93.7]*		
Sternum	100.0 [100.0 - 100.0]	100.0 [100.0 - 100.0]	+ G + M	100.0 [100.0 - 100.0]	100.0 [97.5 - 100.0]	+ G + M	100.0 [90.0 - 100.0]	100.0 [90.0 - 100.0]	+ G + M	80.0 [70.0 - 90.0]*	90.0 [90.0 - 100.0]	+ G + M
Head	100.0 [100.0 - 100.0]			100.0 [100.0 - 100.0]			100.0 [96.3 - 100.0]			80.0 [66.3 - 90.0]		
Shoulder (right)	100.0 [100.0 - 100.0]	100.0 [100.0 - 100.0]	+ G + M	100.0 [100.0 - 100.0]	100.0 [100.0 - 100.0]	+ G + M	95.0 [80.0 - 100.0]	100.0 [96.3 - 100.0]	+ G + M	80.0 [70.0 - 80.0]*	90.0 [86.3 - 100.0]	+ G + M
Shoulder (left)	100.0 [100.0 - 100.0]			100.0 [100.0 - 100.0]			100.0 [96.3 - 100.0]			85.0 [80.0 - 93.7]*		
Upper Arm (right)	100.0 [100.0 - 100.0]			100.0 [100.0 - 100.0]			90.0 [76.3 - 100.0]			75.0 [70.0 - 80.0]*		
Upper Arm (left)	100.0 [100.0 - 100.0]			100.0 [100.0 - 100.0]			90.0 [76.3 - 100.0]			80.0 [66.3 - 90.0]*		
Shank (right)	100.0 [100.0 - 100.0]			100.0 [100.0 - 100.0]			100.0 [90.0 - 100.0]			100.0 [96.3 - 100.0]		
Shank (left)	100.0 [100.0 - 100.0]			100.0 [100.0 - 100.0]			100.0 [86.3 - 100.0]			90.0 [76.3 - 100.0]*		
Foot (right)	100.0 [100.0 - 100.0]			100.0 [100.0 - 100.0]			100.0 [90.0 - 100.0]			80.0 [80.0 - 100.0]*		
Foot (left)	100.0 [100.0 - 100.0]			100.0 [100.0 - 100.0]			100.0 [96.3 - 100.0]			80.0 [76.3 - 90.0]*		
# of Subjects	0			3			7			25		